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Advances in Driver Monitoring: A Review of Liveness Detection Techniques

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Abstract: Driver fatigue significantly contributed to traffic accidents, especially in countries with complex road characteristics like Indonesia. The research emphasized the importance of raising public awareness, developing improved detection technologies, and enforcing strict regulations. Various methods, including computer vision and physiological monitoring, were evaluated to detect driver fatigue and enhance safety through early warnings and advanced detection systems in vehicles. A systematic literature review (SLR) analyzed recent advancements, identified relevant articles, and synthesized findings to highlight current trends, gaps, and potential improvements in driver fatigue detection technology. The study found that driver monitoring systems had played a significant role in reducing traffic accidents, highlighting the importance of enhancing public awareness, advancing monitoring technologies, and enforcing strict regulations. Various methods, including computer vision and physiological monitoring, had been evaluated for their effectiveness in monitoring drivers and improving safety through early warnings and advanced detection systems in vehicles. The SLR identified current trends, gaps, and potential improvements in driver monitoring technology. Future research needed to focus on integrating various evaluation metrics, enhancing physiological monitoring techniques, optimizing overall system performance, and improving user experience. Additionally, interdisciplinary approaches and real-time data analysis and integration with existing vehicle systems were required to create more effective, efficient, and reliable driver monitoring systems, ultimately enhancing driving safety.

Keywords: *Driver Monitoring; Detection; Computer Vision; Safety Driving; Systematic Literature Review*

Introduction

Statistical data revealed that driver fatigue had been identified as the primary factor contributing to traffic accidents in multiple countries, including the United States, Australia, and India[1]–[4]. Moreover, the intricacy and distinctive characteristics of roads in Indonesia had an impact on driver attentiveness[5], thereby escalating the risk of accidents[6]. Consequently, it became imperative to heighten public awareness[1], [7]–[9] and advance technology to decrease the incidence of accidents while enforcing robust regulations to ensure road safety, particularly by emphasizing driver focus and coordination during driving. Fatigue among drivers has been one of the main factors contributing to traffic accidents[2], [10], [11]. This condition led to decreased alertness and response from drivers, which ultimately could cause fatal accidents[9], [12].Therefore, detecting driver[1], [2], [12]–[21] activity or alertness has become a major focus in efforts to improve driving safety[2], [20], [21]. Various methods have been proposed to detect driver fatigue, including the use of physiological markers and computer vision techniques[22]–[24].The development of a computer vision-based driver fatigue detection system involved the identification of the driver's facial features and eyes[25]–[28], assessing the blink rate[1] as an indicator of decreased alertness[5], [16], [24], [29]. Its objective was to detect driver distraction or drowsiness[2], [19], [30]. The integration of activity detection technology into driver assistance systems could identify early signs of fatigue and provide early warnings to drivers[2], [31], thereby reducing the risk of accidents. Additionally, this technology enables the use of multi-modal information such as radar and millimeter-wave vision to improve the accuracy and robustness of detection systems, particularly in the context of autonomous vehicles[28], [32]–[35]. The efficacy of face recognition technology in various applications, such as surveillance systems[36]–[38], drowsiness detection[2], [3], [5], [11], [16], [20], [24], [26], [29], [39]–[45], and mask usage detection[46], was evaluated based on accuracy and execution time[26]. Simple and efficient face recognition systems were achieved by considering variations in facial expressions[15], [21], [24], [26], [28]–[30], [39], [41], [44], [47], [48], positions[49], and rotations[32], [50] and by reducing the size of features[13], [34], [51], [52] and databases through the utilization of facial symmetry in Viola-Jones[4], [16], [26], [39], [42], [43], [53] and Principal Component Analysis (PCA)[54], [55], resulting in high success rates. Vector feature comparison using the cosine distance function, deep multi-task learning with D-CNN[4], local binary pattern (LBP)[56], [57], Convolutional Neural Network (CNN)[17], [44], and Amazon Rekognition were also explored. The implementation of face recognition in surveillance systems employed Raspberry Pi and Pi Camera[17], [44]. Real-time driver fatigue detection involved monitoring specific areas of the driver's eyes, specifically the nose and lips[5], [29]. To address challenges posed by insufficient lighting conditions[21], the adaptive attenuation quantification retinex (AAQR) method was employed. However, there are several challenges in developing activity detection systems. These challenges include difficulties in distinguishing living objects from visual disturbances and preventing spoofing attacks[35], [58], [59]. Therefore, much research has focused on developing more advanced methods, such as deep learning and multi-channel facial activity detection, to enhance detection accuracy and security. The integration of Human-Machine Interface (HMI)[60] systems in vehicles connected with activity detection technology also has the potential to provide more accurate speed limit warnings, thus improving overall driver safety. With these technological advancements, it is expected that activity detection systems will significantly contribute to reducing traffic accidents and enhancing driver safety on the road. The purpose of this research is to develop a comprehensive understanding of the current state of driver fatigue detection technologies and to identify gaps and opportunities for improvement. By conducting a semantic literature review, this study aims to position the research within the broader context of existing studies and technological advancements. The key research problems addressed include identifying the most effective methods for detecting driver fatigue, understanding the challenges associated with implementing these technologies in real-world scenarios, and exploring potential solutions to enhance the accuracy and reliability of detection systems.

Method

Facial expressions[5], [12], [17], [20], [21], [24], [26], [29], [39], [41], [44], [47], [48], [61] were employed as a form of nonverbal communication, conveying information about an individual's emotional state. Driving behaviors and habits shaped drivers' various driving styles, experiences, and emotions[8], [20]. While detecting and recognizing human emotions has been significant in computer vision (CV) and artificial intelligence (AI)[62], identifying driver facial expressions is crucial for road safety and security. Using readily available cameras, facial detection could be implemented easily, cost-effectively, and commonly. However, challenges arose in detecting facial features like hair, glasses, hats, and other accessories due to variations in lighting, facial expressions, and individual body postures. Although these systems had applications in security and control systems, noise often occurred during face detection in digital images. Real-time driver sleep detection models monitored driver behavior to detect drowsiness. Object detection systems achieved accuracy levels of up to 80%[30], [45], [49], [63]. However, these methods required expensive sensors for data processing[24], [64]. To address these needs, affordable, portable, secure, fast, and accurate systems were proposed. Successful face detection was achieved within distances of 1-2 meters[65], [66]. The tested system achieved an accuracy of 82% indoors and a 72.8% positive detection rate outdoors. OpenCV provided highly efficient object detection functions based on the Haar cascade Viola-Jones classifier for frontal face detection, face recognition using Eigenface and Haar in OpenCV, and eye detection on the Android platform for comparing closed-eye frequencies[67], [68]. The Viola-Jones algorithm consisted of four stages: integral image, Haar features, cascade, and AdaBoost[26], [43], [52]. The Haar cascade method[19], [35] is commonly employed for face detection due to its efficient image processing and rapid identification of facial features. However, the reliability of face detection using the Haar cascade method for driver facial detection may be affected by environmental disturbances, such as low light, shadows, or changes in lighting conditions[15], [37]–[39], [69]. This algorithm utilizes the AdaBoost method[34] to train the face detector, employing a combination of different weak classifiers to form a strong classifier.

Various approaches to detecting driver distraction had been developed, including the use of physiological, physical, driver performance indicators, and hybrid approaches, each with its specific techniques. Although in-vehicle sensors and the Internet of Things (IoT)[40], [70] were commonly used for data collection, further attention was required for data specific to driver behavior. Technologies such as real-time eye-tracking systems[60], [71], heart rate sensors[72], and smartphone applications were effectively used to detect driver distraction[30], [41], [64], [71], [73], [74]. Additionally, proactive measures like active probes in vehicles had been proposed to detect driver drowsiness, proving more effective than traditional monitoring methods. The integration of neural network-based methodologies[13], [74] had been key in studying driver biometrics and behavior[17], [75], contributing to the development of more advanced monitoring systems[26], [30]. Despite significant progress, current monitoring systems still faced challenges, necessitating further discussion on future solutions to enhance their effectiveness and reliability.

This research utilized a systematic literature review (SLR) method to explore recent advancements in driver liveness detection. The initial step involved defining an appropriate scope[74], [76]–[78], focusing on current technologies[26], [30], [49], [64], [70], [79]–[81] and techniques[16], [21], [24], [39], [46], [53], [74], [78] used in related literature, such as physiological signal[18], [72] detection and computer data processing techniques[12], [21], [24], [26], [30], [44], [46], [52], [74], [81]–[84]. A carefully designed search protocol enabled the identification of relevant articles from databases like Scopus, using specific keywords such as "driver liveness detection" and "face liveness detection." Article selection was based on inclusion criteria that encompassed recent publication years, types of experimental studies, and the detection techniques used (See in **Figure 1**). Data extracted from the selected articles were then analyzed to compare the detection methods used, types of data analyzed, as well as evaluation results and key findings from each study. The results of this SLR were synthesized to identify current trends, knowledge gaps, and potential advancements in driver liveness detection technology to enhance driving safety.

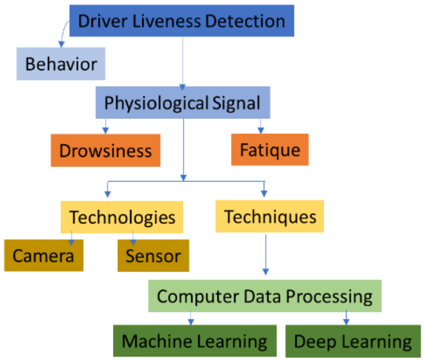

Figure 1. Schematic Flow of Research Thinking

Result and Discussion

Fatigue driving caused many accidents and challenged driver alertness and automobile control, making driver fatigue detection systems a necessity. Traditional invasive approaches, such as analyzing electroencephalography signals with head electrodes, were found to be inconvenient for drivers. Driver fatigue was widely recognized as a major cause of motor vehicle accidents, highlighting the need to reduce fatigue driving crashes. Many studies evaluating the crash risk of fatigue driving and developing detection systems used observer rating of drowsiness (ORD) as a reference standard. Additionally, driver emotion classification raised awareness of driving habits, helping drivers recognize and correct their poor behaviors to prevent future accidents. Given that fatigue in drivers was a major cause of fatal road accidents, timely detection and alerting were crucial. Researchers developed several techniques to detect and warn drivers of fatigue. Physiological signal indices could accurately reflect fatigue levels, but contact detection methods significantly affected driving. This paper identifies current trends, knowledge gaps, and potential advancements in driver fatigue technology to enhance safe driving by conducting a semantic literature review from 2019 to 2023. A systematic literature review was conducted on driver liveness detection to understand its status, research methods, and analyses that have been developed, particularly to enhance driving safety. The Scopus database was selected for this review, and the workflow is illustrated in the accompanying diagram (see in **Figure 2**).

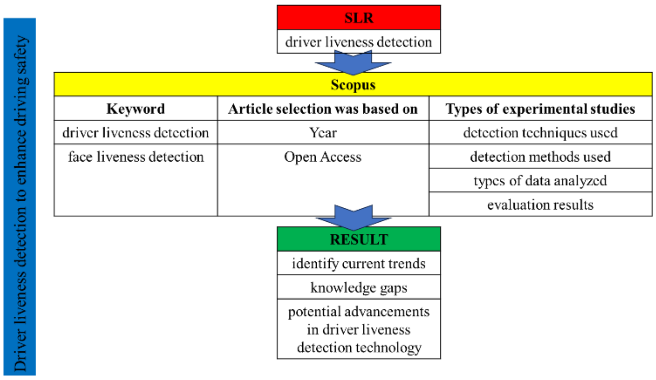

Figure 2. Workflow for Literature Search on Driver Liveness Detection

A systematic review was carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) process[85]. Template PRISMA was downloaded from the site https://estech.shinyapps.io/prisma_flowdiagram/. Related manuscripts were found using Scopus database. The proposed approach was divided into two phases. The first phase used Boolean operators AND/OR to identify search terms "driver liveness detection" and "face liveness detection". The findings of the systematic analysis were summarized in this section. It presented the responses to the mentioned research questions based on the findings of this review procedure, which followed an examination and analysis of 26 papers see in **Figure 3**.

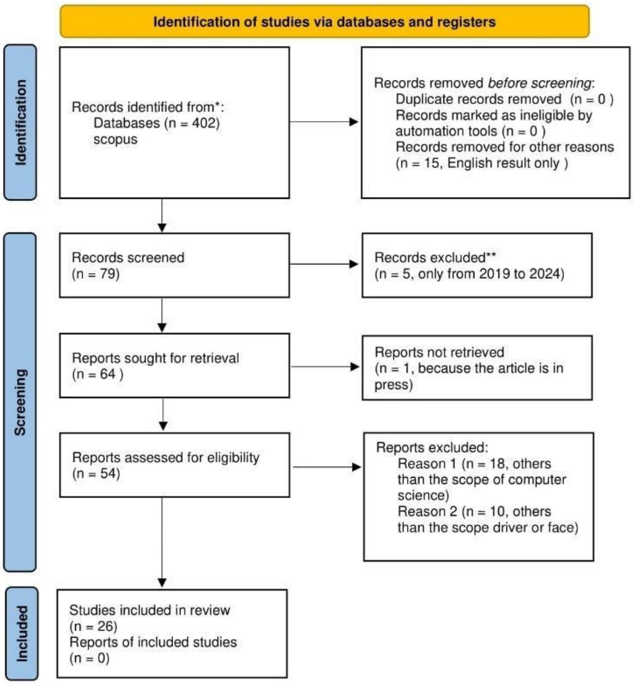

Figure 3. Flowchart identifies and selects studies for systematic review using the PRISMA approach

From the 26 papers found, terms/keywords (**Table 1**) were sorted by publication year, from the most recent to the oldest.

Table 1. Terms/Keywords were Sorted by Publication Year, from the Most Recent to the Oldest

NO	LABEL	CLUSTER	WEIGHT<OCCURRENCES>	SCORE<AVG, PUB, YEAR>
1	Three-dimensional display	6	6	2023
2	Features extraction	6	9	2022,8889
3	Machine-learning	5	6	2022,8333
4	Performance	7	5	2022,6
5	'Current	7	6	2022,5
6	Three dimensional displays	6	7	2022,2857
7	Detection models	2	5	2022,2
8	Mask attack	6	7	2022,1429
9	Faces detection	2	11	2021,9091
10	Multi-modal	4	7	2021,8571
11	Features fusions	3	5	2021,8
12	Face verification	6	9	2021,7778

13	3d masks	6	10	2021,6
14	Real- time	7	5	2021,6
15	Smart phones	7	5	2021,6
16	Transfer learning	5	8	2021,5
17	Identity verification	6	5	2021,4
18	Image reconstruction	7	5	2021,4
19	Neural-networks	3	7	2021,2857
20	Internet of things	5	11	2021,2727
21	Crime	5	5	2021,2
22	Intelligent systems	4	6	2021,1667
23	Statistical tests	1	9	2021,1111
24	Fake detection	7	27	2021,037
25	Learning algorithms	2	5	2021
26	Feature fusion	3	6	2021
27	Rppg	6	7	2021
28	Facial recognition systems	8	11	2021
29	Deep learning	6	74	2020,9054
30	Detection system	7	10	2020,9
31	Face anti-spoofing	6	30	2020,8667
32	Detection accuracy	3	5	2020,8
33	Infrared imaging	3	5	2020,8
34	Machine learning	5	19	2020,7895
35	Convolutional neural networks	1	41	2020,7805
36	Antispoofing	6	44	2020,7273
37	Cnn	3	7	2020,7143
38	Presentation attack detection	6	11	2020,6364
39	Photoplethysmography	6	8	2020,625
40	Face presentation attack detection	6	10	2020,6
41	Attack detection	6	27	2020,5926
42	Presentation attack	2	10	2020,5
43	Specular reflections	6	5	2020,4
44	Extraction	5	7	2020,2857
45	Face	4	20	2020,2
46	Human faces	7	5	2020,2
47	Quality control	9	5	2020,2
48	Human computer interaction	2	6	2020,1667
49	Benchmarking	6	6	2020,1667
50	Automation	4	7	2020,1429
51	Facial recognition	3	20	2020,1
52	Convolution	1	35	2020,0286
53	Deep neural networks	1	26	2020
54	Network architecture	1	8	2020
55	Eye detection	2	6	2020
56	Histogram of oriented gradients	2	6	2020
57	Convolutional neural network	1	34	2019,9706
58	Security systems	9	14	2019,9286
59	Face detection	2	18	2019,8333
60	Textures	1	34	2019,7353
61	Biometric	5	14	2019,7143
62	Face biometrics	9	7	2019,7143
63	Authentication methods	1	6	2019,6667
64	Smartphones	7	14	2019,6429
65	Learning systems	5	32	2019,625
66	3d modeling	2	5	2019,6
67	Eye protection	2	5	2019,6
68	Facial expressions	2	5	2019,6
69	Gesture recognition	5	5	2019,6
70	Benchmark datasets	6	5	2019,6
71	Convolution neural network	2	14	2019,5714
72	Classification (of information)	1	30	2019,5333
73	Stereo image processing	7	6	2019,5
74	Lighting conditions	8	9	2019,4444
75	Infrared devices	3	7	2019,4286
76	Heart	6	7	2019,4286
77	Diffusion	3	5	2019,4
78	Face liveness detection	1	79	2019,3165
79	Image enhancement	2	19	2019,3158

80	Face spoofing detection	1	10	2019,3
81	State of the art	6	9	2019,2222
82	Face authentication	7	26	2019,1923
83	Access control	8	16	2019,1875
84	Cameras	7	28	2019,0357
85	Biometric based authentication	1	6	2019
86	Local binary pattern	1	5	2019
87	Video signal processing	3	5	2019
88	Fingerprint	4	7	2019
89	Biometric identifications	5	6	2019
90	Biometric recognition	5	7	2019
91	Spoof detection	5	6	2019
92	Cryptography	7	5	2019
93	Face authentication system	7	18	2019

Terms/keywords were sorted based on publication year from the newest to the oldest and processed into word clouds using the HP 14S-DK0127AU laptop. The specifications of the laptop, which featured an AMD Ryzen 3-3200U processor, 8GB RAM, 512GB SSD, and a 14" Full HD display, were used to process word clouds with Google Colab for text data visualization (See in Figure 4).

Figure 4. Word Clouds of Terms/Keywords Sorted by Publication Year (Newest to Oldest)

The filtered papers span from 2019 to 2024, with the majority published in 2023. This distribution highlights the recent focus and development in driver liveness detection research over the past few years, as shown in **Table 2.**

Table 2. Distribution of Filtered Papers by Publication Year

Year	Total	Used in Literature
2024	2	[21][86]
2023	16	[5], [6], [8], [12], [18], [30], [46], [70], [72], [84], [87]–[92]
2022	3	[93]–[95]
2021	2	[96], [97]
2020	1	[98]
2019	2	[99], [100]

The research has seen advancements with the adoption of various detection techniques: Artificial Intelligence was applied in 10 instances, Machine Learning in 5 instances, Deep Learning in 8 instances, and Literature Review in 3 instances (see in **Table 3**).

Table 3. Utilization of Detection Techniques in Research

Detection Technique Used	Total	Used in Literature
Artificial Intelligence	10	[5], [6], [18], [21], [70], [72], [86], [88], [90], [95], [100]
Machine Learning	5	[30], [46], [94], [97], [99]
Deep Learning	8	[12], [87], [89], [91]–[93], [96], [98]
Literature Review	3	[8], [83], [84]

Different detection techniques (Table 4) were analyzed for their effectiveness in identifying various driver states. Techniques for detecting fatigue and drowsiness were most frequently used, each cited in 8 studies. Emotion detection techniques were mentioned in 4 studies, while physiological monitoring techniques appeared in 6 studies. This indicates a strong focus on fatigue and drowsiness detection but also highlights the importance of monitoring emotional and physiological states.

Table 4. Detection Techniques for Driver States and Their Frequency of Use in Research

Detection Technique For	Total	Used in Literature
Fatique	8	[13], [18], [46], [84], [86], [87], [95], [100]
Drowsiness	8	[5], [6], [12], [46], [70], [89], [91], [99]
Emotion	4	[8], [89], [90], [94]
Physiological	6	[6], [18], [21], [30], [72], [99]

The analysis of data types in driver monitoring systems varied significantly, with face recognition data being the most frequently analyzed, utilized in 18 studies (see in **Table 5**). This technique proved highly effective for real-time monitoring, providing crucial information about the driver's alertness and identity. Visual perception and intelligent robotics data were used in one study each, indicating an emerging interest in these areas. Problem-solving and search strategies were cited in two studies, showing some application in decision-making processes within driver monitoring systems. Machine learning techniques showed diverse usage: linear/logistic regression was used in three studies, support vector machines in two, and k-nearest neighbors in two, reflecting their role in analyzing and predicting driver states. Ensemble methods were also popular, used in three studies, showcasing their ability to improve prediction accuracy by combining multiple models. Deep learning techniques, particularly convolutional neural networks (CNN), were widely used, cited in eight studies, due to their ability to handle complex image data for driver monitoring. Recurrent neural networks (RNN) and adaptive resonance theory were each mentioned in one study, indicating their potential in temporal data analysis and pattern recognition. Despite these advancements, several challenges and gaps remained in the field. The integration of diverse data types, such as visual perception and intelligent robotics, needed improvement to create more comprehensive monitoring systems. Most studies focused on accuracy, with fewer addressing precision, recall, and F-measure, highlighting the need for a more holistic approach to evaluation. Ensuring real-time data processing and scalability of systems remained a challenge, especially with the large data volumes generated by techniques like CNNs. Improving user interface and acceptance was crucial for practical implementation. To address these challenges, future research and development could focus on advanced integration techniques, such as combining face recognition with physiological monitoring, to enhance system robustness and reliability. Creating comprehensive evaluation frameworks that include a wider range of metrics would provide a more complete picture of system performance. Optimizing algorithms for real-time data processing would ensure efficient large-scale deployment. Emphasizing user-centric design principles would improve usability and acceptance, making systems more intuitive and less intrusive. Encouraging interdisciplinary research that combined insights from artificial intelligence, machine learning, human factors, and automotive engineering would develop more effective monitoring solutions. By addressing these areas, future research could significantly improve the effectiveness, efficiency, and reliability of driver monitoring technologies, ultimately making roads safer and reducing the risk of accidents.

Table 5. Analysis of Data Types and Techniques Used in Driver Monitoring Systems

	Type Of Data Analyzed	Total	Used in Literature
Artificial Intelligence	Natural Language Processing (NLP)	0	
	Visual Perception	1	[6]
	Intelligent Robotics	1	[70]
	Automated Programming	0	
	Knowledge Repsentation	0	
	Expert System	0	
	Planning and Schedulling	0	
	Face Recognition	18	[8], [13], [17], [21], [30], [70], [86]–[92], [94]–[96], [98], [100]
	Problem Solving and Search Strategies	2	[83], [95]
Machine Learning	Linear/Logistic Regression	3	[90], [93], [99]
	Support Vector Machine	2	[46], [99]
	K-Nearest Neighbors	2	[99], [100]
	Decision Trees	0	
	K-Means Clustering	0	
	Principal Component Analysis	0	
	Automatic Reasoning	1	[8]
	Random Forest	0	
	Ensemble Method	3	[8], [91], [94]
	Naive Bayes Classification	0	
	Anomaly Detection	0	
	Reinforcement Learning	0	
Neural Networks	Boltzmann Machines	0	
	Multilayer Perception	0	
	Self-Organizing Maps	0	
	Radial Basis Function Networks	0	
	Recurrent Neural Networks	1	[8]
	Autoencoders	0	
	Hopfield Networks	0	
	Modural Neural Networks	0	
	Adaptive Resonance Theory	2	[13], [95]
Deep Learning	Convolutional Neural Network	8	[8], [17], [21], [89], [92], [93], [96], [98]
	Recurrent Neural Networks	1	[8]
	Generative Adversarial Networks	0	
	Long Short-Term Memory Networks	0	
	Deep Reinforcement	0	
	Transformer Models	0	
	Deep Autoencoders	0	
	Deep Belief Networks	0	

In recent years, studies on driver monitoring have produced heatmaps (see in **Figure 5**) illustrating significant correlations between various detection techniques and data types. The heatmaps revealed that Natural Language Processing (NLP) was strongly associated with fatigue, drowsiness, emotion detection, and artificial intelligence, indicating its widespread use in analyzing human conditions and AI. Face recognition demonstrated a strong link with physiological data, highlighting its primary application in physiological analysis. Problem-solving and search strategies showed some association with artificial intelligence, reflecting their use in AI-based problem-solving strategies. Meanwhile, visual perception and intelligent robotics exhibited limited correlations with physiological data, suggesting more restricted applications in this context. Overall, the heatmaps depicted close relationships between specific detection techniques and data types, uncovering key trends and focal points in research and applications of detection and data analysis technologies.

Based on the findings, future initiatives should aim to advance NLP applications for detecting fatigue, drowsiness, emotion, and AI, and to enhance the analysis of physiological data in face recognition. Expanding AI-based problem-solving strategies and applying them to driving safety is essential. Additionally, there is a need to extend the use of visual perception and intelligent robotics in physiological analysis. Promoting interdisciplinary research will help create comprehensive monitoring systems, while investments in data integration and advanced analytical methods are crucial. It is also important to focus on user-centric design to improve the usability, reliability, and acceptance of driver monitoring systems, ultimately enhancing driving safety.

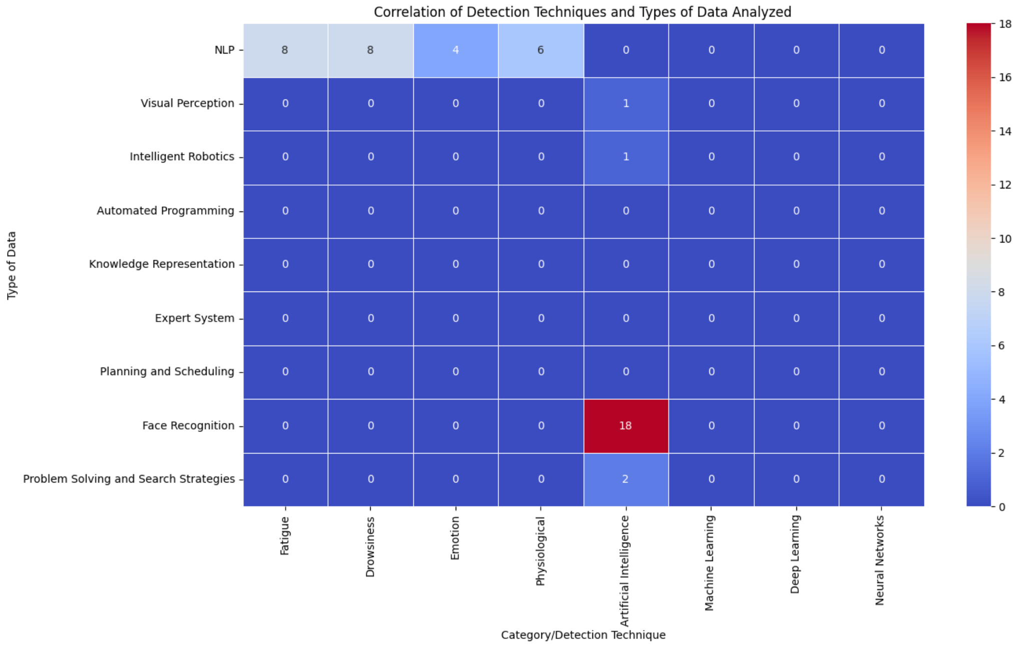

Figure 5. Heatmap Illustrating Correlations Between Detection Techniques and Data Types in Driver Monitoring Studies

Based on the evaluation results and references from the literature (see in **Table 6**), it was clear that accuracy was the most commonly used metric to assess the performance of driver drowsiness and emotion detection systems. However, precision, recall, and F-measure were less frequently implemented, indicating a need for more comprehensive evaluations. Physiological monitoring had been a significant focus area, highlighting the importance of tracking physiological indicators of driver fatigue or drowsiness. System performance, including efficiency and reliability, and user experience were also crucial aspects emphasized in several studies. For future development, integrating various evaluation metrics to provide a more holistic view of system performance was necessary. Enhancing physiological monitoring techniques, optimizing overall system performance, and improving user experience were essential steps. Additionally, interdisciplinary approaches and real-time data analysis and integration with existing vehicle systems were required to create more effective, efficient, and reliable driver monitoring systems, ultimately enhancing driving safety. The future challenge lay in integrating these diverse methodologies to develop more comprehensive and robust driver monitoring systems. There was a need for further research to address the gaps in applying advanced deep learning techniques and multimodal data integration for real-time, accurate, and reliable detection of driver states. The integration of interdisciplinary approaches and user-centric designs also remained critical to improving the usability and acceptance of these systems, ultimately enhancing driving safety.

Table 6. Evaluation Metrics and Focus Areas Cited in Driver Monitoring System Research

Evalution Results	Total	Used in Literature
Accuracy	14	[5], [8], [95], [98]–[100], [30], [46], [70], [86], [87], [89], [91], [93]
Precision	2	[5], [87]
Recall	2	[5], [87]
F-Measure	2	[5], [87]
Physiological Monitoring	9	[5], [12], [18], [21], [29], [72], [94], [96], [97]
System Performance	5	[6], [12], [88], [90], [97]
User Experience	4	[12], [70], [96], [97]

Conclusions

The study discovered that driver monitoring systems had played a significant role in reducing traffic accidents, particularly in countries with complex road characteristics like Indonesia. It highlighted the importance of raising public awareness, advancing monitoring technologies, and enforcing strict regulations. Various methods, including computer vision and physiological monitoring, had been evaluated for their effectiveness in monitoring drivers and improving safety through early warnings and advanced detection systems in vehicles. A systematic literature review (SLR) had analyzed recent advancements, identified relevant studies, and synthesized findings to highlight current trends, gaps, and potential improvements in driver monitoring technology. Future research needed to focus on integrating various evaluation metrics, enhancing physiological monitoring techniques, optimizing overall system performance, and improving user experience. Additionally, interdisciplinary approaches and real-time data analysis and integration with existing vehicle systems were required to create more effective, efficient, and reliable driver monitoring systems, ultimately enhancing driving safety.

References

[1] M. Chakraborty and A. N. H. Aoyon, “Implementation of Computer Vision to detect driver fatigue or drowsiness to reduce the chances of vehicle accident,” *1st Int. Conf. Electr. Eng. Inf. Commun. Technol. ICEEICT 2014*, 2014, doi: 10.1109/ICEEICT.2014.6919054.

[2] I. R. Adochiei *et al.*, “Drivers’ drowsiness detection and warning systems for critical infrastructures,” *2020 8th E-Health Bioeng. Conf. EHB 2020*, pp. 14–17, 2020, doi: 10.1109/EHB50910.2020.9280165.

[3] S. Dey, S. A. Chowdhury, S. Sultana, M. A. Hossain, M. Dey, and S. K. Das, “Real Time Driver Fatigue Detection Based on Facial Behaviour along with Machine Learning Approaches,” *2019 IEEE Int. Conf. Signal Process. Information, Commun. Syst. SPICSCON 2019*, pp. 135–140, 2019, doi: 10.1109/SPICSCON48833.2019.9065120.

[4] V. R. Reddy Chirra, S. R. Uyyala, and V. K. Kishore Kolli, “Deep CNN: A machine learning approach for driver drowsiness detection based on eye state,” *Rev. d’Intelligence Artif.*, vol. 33, no. 6, pp. 461–466, 2019, doi: 10.18280/ria.330609.

[5] B. Akrout and S. Fakhfakh, “How to Prevent Drivers before Their Sleepiness Using Deep Learning-Based Approach,” *Electron.*, vol. 12, no. 4, pp. 1–19, 2023, doi: 10.3390/electronics12040965.

[6] Y. Uchiyama *et al.*, “Convergent validity of video-based observer rating of drowsiness, against subjective, behavioral, and physiological measures,” *PLoS One*, vol. 18, no. 5 May, pp. 1–16, 2023, doi: 10.1371/journal.pone.0285557.

[7] W. Shi, J. Li, Y. Ding, and K. Zhou, “Research on Intelligent Access Control System Based on Interactive Face Liveness Detection and Machine Vision,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 563, no. 5, 2019, doi: 10.1088/1757-899X/563/5/052094.

[8] K. Zaman *et al.*, “A novel driver emotion recognition system based on deep ensemble classification,” *Complex Intell. Syst.*, vol. 9, no. 6, pp. 6927–6952, 2023, doi: 10.1007/s40747-023-01100-9.

[9] S. Dey, S. A. Chowdhury, S. Sultana, M. A. Hossain, M. Dey, and S. K. Das, “Real Time Driver Fatigue Detection Based on Facial Behaviour along with Machine Learning Approaches,” *2019 IEEE Int. Conf. Signal Process. Information, Commun. Syst. SPICSCON 2019*, pp. 135–140, 2019, doi: 10.1109/SPICSCON48833.2019.9065120.

[10] C. L. Chen, C. Y. Liao, R. C. Chen, Y. W. Tang, and T. F. Shih, “Bus drivers fatigue measurement based on monopolar EEG,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10192 LNAI, pp. 308–317, 2017, doi: 10.1007/978-3-319-54430-4_30.

[11] Y. Ed-Doughmi, N. Idrissi, and Y. Hbali, "Real-time system for driver fatigue detection based on a recurrent neuronal network," *J. Imaging*, vol. 6, no. 3, 2020, doi: 10.3390/jimaging6030008.

[12] P. Sowmyashree and J. Sangeetha, "Multistage End-to-End Driver Drowsiness Alerting System," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 4, pp. 464–473, 2023, doi: 10.14569/IJACSA.2023.0140452.

[13] H. Zheng, Y. Wang, and X. Liu, "Adaptive Driver Face Feature Fatigue Detection Algorithm Research," *Appl. Sci.*, vol. 13, no. 8, 2023, doi: 10.3390/app13085074.

[14] G. D'Angelo, A. Castiglione, and F. Palmieri, "A Cluster-Based Multidimensional Approach for Detecting Attacks on Connected Vehicles," *IEEE Internet Things J.*, vol. 8, no. 16, pp. 12518–12527, 2021, doi: 10.1109/JIOT.2020.3032935.

[15] Y. Shang, M. Yang, J. Cui, L. Cui, Z. Huang, and X. Li, "Driver Emotion and Fatigue State Detection Based on Time Series Fusion," *Electron.*, vol. 12, no. 1, 2023, doi: 10.3390/electronics12010026.

[16] V. P. Sharma, J. S. Yadav, and V. Sharma, "Deep convolutional network based real time fatigue detection and drowsiness alertness system," *Int. J. Electr. Comput. Eng.*, vol. 12, no. 5, pp. 5493–5500, 2022, doi: 10.11591/ijece.v12i5.pp5493-5500.

[17] H. A. Ahmed, M. A. Noaman Al-Hayanni, and M. S. Croock, "Intelligent and secure real-time auto-stop car system using deep-learning models," *Int. J. Electr. Comput. Eng. Syst.*, vol. 15, no. 1, pp. 31–39, 2024, doi: 10.32985/ijeces.15.1.4.

[18] J. J. Bi, X. P. Qin, D. J. Hu, and C. Y. Xu, "Fatigue driving detection method based on IPPG technology," *Promet - Traffic Transp.*, vol. 35, no. 4, pp. 540–551, 2023, doi: 10.7307/ptt.v35i4.134.

[19] S. Junaedi and H. Akbar, "Driver Drowsiness Detection Based on Face Feature and PERCLOS," *J. Phys. Conf. Ser.*, vol. 1090, no. 1, 2018, doi: 10.1088/1742-6596/1090/1/012037.

[20] M. H. Alkinani, W. Z. Khan, and Q. Arshad, "Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges," *IEEE Access*, vol. 8, pp. 105008–105030, 2020, doi: 10.1109/ACCESS.2020.2999829.

[21] J. Hollósi, Á. Ballagi, G. Kovács, S. Fischer, and V. Nagy, "Bus Driver Head Position Detection Using Capsule Networks under Dynamic Driving Conditions," *Computers*, vol. 13, no. 3, 2024, doi: 10.3390/computers13030066.

[22] W. Zhang, X. Li, Q. Song, and W. Lu, "A face detection method based on image processing and improved adaptive boosting algorithm," *Trait. du Signal*, vol. 37, no. 3, pp. 395–403, 2020, doi: 10.18280/ts.370306.

[23] S. Liu, Y. Song, M. Zhang, J. Zhao, S. Yang, and K. Hou, "An identity authentication method combining liveness detection and face recognition," *Sensors (Switzerland)*, vol. 19, no. 21, 2019, doi: 10.3390/s19214733.

[24] V. Valsan A, P. P. Mathai, and I. Babu, "Monitoring driver's drowsiness status at night based on computer vision," *Proc. - IEEE 2021 Int. Conf. Comput. Commun. Intell. Syst. ICCCIS 2021*, pp. 989–993, 2021, doi: 10.1109/ICCCIS51004.2021.9397180.

[25] A. Hassan and S. Viriri, "Deeply Learned Invariant Features for Component-based Facial Recognition," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 11, pp. 636–644, 2022, doi: 10.14569/IJACSA.2022.0131174.

[26] M. Ameen Sulaiman and I. Sarhan Kocher, "A systematic review on Evaluation of Existing Face Eyes Detection Algorithms for Monitoring Systems," *Acad. J. Nawroz Univ.*, vol. 11, no. 1, pp. 57–72, 2022, doi: 10.25007/ajnu.v11n1a1234.

[27] J. W. Ong, W. J. Chew, and S. K. Phang, "The application of image processing for monitoring student's attention level during online class," *J. Phys. Conf. Ser.*, vol. 2120, no. 1, 2021, doi: 10.1088/1742-6596/2120/1/012028.

[28] T. Li, T. Zhang, and Q. Li, "Train Driver Fatigue Detection Using Eye Feature Vector and Support Vector Machine," *Int. J. Circuits, Syst. Signal Process.*, vol. 16, pp. 1007–1017, 2022, doi: 10.46300/9106.2022.16.123.

[29] B. Akrout and W. Mahdi, "A novel approach for driver fatigue detection based on visual characteristics analysis," *J. Ambient Intell. Humaniz. Comput.*, vol. 14, no. 1, pp. 527–552, 2023, doi: 10.1007/s12652-021-03311-9.

[30] W. Shariff *et al.*, "Neuromorphic Driver Monitoring Systems: A Computationally Efficient Proof-of-Concept for Driver Distraction Detection," *IEEE Open J. Veh. Technol.*, vol. 4, no. October, pp. 836–848, 2023, doi: 10.1109/OJVT.2023.3325656.

[31] Y. Zhou, L. Zhu, J. Yi, T. H. Luan, and C. Li, "On Vehicle Fault Diagnosis: A Low Complexity Onboard Method," *2020 IEEE Glob. Commun. Conf. GLOBECOM 2020 - Proc.*, 2020, doi:

10.1109/GLOBECOM42002.2020.9322534.

[32] A. H. T. Al-Ghrairi, A. A. Mohammed, and E. Z. Sameen, "Face detection and recognition with 180 degree rotation based on principal component analysis algorithm," *IAES Int. J. Artif. Intell.*, vol. 11, no. 2, pp. 593–602, 2022, doi: 10.11591/ijai.v11.i2.pp593-602.

[33] A. H. Thary Al-Ghrairi, N. H. F. Al-Anbari, and E. Z. Sameen, "Realtime human face tracking and recognition system on uncontrolled environment," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 4, pp. 4246–4255, 2023, doi: 10.11591/ijece.v13i4.pp4246-4255.

[34] F. Wang, X. Chen, D. Wang, and B. Yang, "An improved image-based iris-tracking for driver fatigue detection system," *Chinese Control Conf. CCC*, pp. 11521–11526, 2017, doi: 10.23919/ChiCC.2017.8029198.

[35] A. K. Pandey and R. Pandey, "Segment-wise Quality Evaluation for Identification of Face Spoofing," *Int. J. Image, Graph. Signal Process.*, vol. 12, no. 1, pp. 30–37, 2020, doi: 10.5815/ijigsp.2020.01.04.

[36] R. Jayaswal and M. Dixit, "Comparative analysis of human face recognition by traditional methods and deep learning in real-time environment," *Proc. - 2020 IEEE 9th Int. Conf. Commun. Syst. Netw. Technol. CSNT 2020*, no. July, pp. 66–71, 2020, doi: 10.1109/CSNT48778.2020.9115779.

[37] F. N. M. Ariff, H. Jaafar, S. N. H. Jusoh, and N. A. F. Haris, "Single and Multiface Detection and Recognition System," *J. Phys. Conf. Ser.*, vol. 2312, no. 1, 2022, doi: 10.1088/1742-6596/2312/1/012036.

[38] M. Singh and A. S. Arora, "A Novel Face Liveness Detection Algorithm with Multiple Liveness Indicators," *Wirel. Pers. Commun.*, vol. 100, no. 4, pp. 1677–1687, 2018, doi: 10.1007/s11277-018-5661-1.

[39] N. N. A. Mangshor, I. A. A. Majid, S. Ibrahim, and N. Sabri, "A real-time drowsiness and fatigue recognition using support vector machine," *IAES Int. J. Artif. Intell.*, vol. 9, no. 4, pp. 584–590, 2020, doi: 10.11591/ijai.v9.i4.pp584-590.

[40] A. K. Biswal, D. Singh, B. K. Pattanayak, D. Samanta, and M. H. Yang, "IoT-based smart alert system for drowsy driver detection," *Wirel. Commun. Mob. Comput.*, vol. 2021, 2021, doi: 10.1155/2021/6627217.

[41] W. Kim, W. S. Jung, and H. K. Choi, "Lightweight driver monitoring system based on multi-task mobilenets," *Sensors (Switzerland)*, vol. 19, no. 14, 2019, doi: 10.3390/s19143200.

[42] K. S. R. Murthy, B. Siddineni, V. K. Kompella, K. Aashritha, B. H. Sri Sai, and V. M. Manikandan, "An Efficient Drowsiness Detection Scheme using Video Analysis," *Int. J. Comput. Digit. Syst.*, vol. 11, no. 1, pp. 573–581, 2022, doi: 10.12785/ijcds/110146.

[43] S. Said, S. AlKork, T. Beyrouthy, M. Hassan, O. E. Abdellatif, and M. Fayek Abdraboo, "Real time eye tracking and detection- A driving assistance system," *Adv. Sci. Technol. Eng. Syst.*, vol. 3, no. 6, pp. 446–454, 2018, doi: 10.25046/aj030653.

[44] S. S. Sharan, R. Viji, R. Pradeep, and V. Sajith, "Driver Fatigue Detection Based on Eye State Recognition Using Convolutional Neural Network," *Proc. 4th Int. Conf. Commun. Electron. Syst. ICCES 2019*, no. Icces, pp. 2057–2063, 2019, doi: 10.1109/ICCES45898.2019.9002215.

[45] Z. Cui, H. M. Sun, R. N. Yin, L. Gao, H. Bin Sun, and R. S. Jia, "Real-time detection method of driver fatigue state based on deep learning of face video," *Multimed. Tools Appl.*, vol. 80, no. 17, pp. 25495–25515, 2021, doi: 10.1007/s11042-021-10930-z.

[46] R. P. N. Budiarti, B. W. Nugroho, N. Ayunda, and S. Sukaridhoto, "Drowsy Eyes and Face Mask Detection for Car Drivers using the Embedded System," *Regist. J. Ilm. Teknol. Sist. Inf.*, vol. 9, no. 1, pp. 86–94, 2023, doi: 10.26594/register.v9i1.2612.

[47] S. Palaniswamy and S. Tripathi, "Emotion recognition from facial expressions using images with pose, illumination and age variation for human-computer/robot interaction," *J. ICT Res. Appl.*, vol. 12, no. 1, pp. 14–34, 2018, doi: 10.5614/itbj.ict.res.appl.2018.12.1.2.

[48] Y. Sun, P. Yan, Z. Li, J. Zou, and D. Hong, "Driver fatigue detection system based on colored and infrared eye features fusion," *Comput. Mater. Contin.*, vol. 63, no. 3, pp. 1563–1574, 2020, doi: 10.32604/CMC.2020.09763.

[49] B. Yu, S. Bao, Y. Zhang, J. Sullivan, and M. Flannagan, "Measurement and prediction of driver trust in automated vehicle technologies: An application of hand position transition probability matrix," *Transp. Res. Part C Emerg. Technol.*, vol. 124, 2021, doi: 10.1016/j.trc.2020.102957.

[50] E. Torres Pereira, H. Martins Gomes, and J. M. De Carvalho, "An approach for multi-pose face detection exploring invariance by training," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 8495 LNCS, pp. 182–191, 2014, doi: 10.1007/978-3-319-07491-7_19.

[51] C. A. Ruiz-Beltrán, A. Romero-Garcés, M. González, A. S. Pedraza, J. A. Rodríguez-Fernández, and A. Bandera, "Real-time embedded eye detection system," *Expert Syst. Appl.*, vol. 194, p. 116505, 2022, doi: 10.1016/j.eswa.2022.116505.

[52] M. ÖZTÜRK, A. KÜÇÜKMANİSA, and O. URHAN, "Drowsiness Detection System Based on Machine Learning Using Eye State," *Balk. J. Electr. Comput. Eng.*, vol. 10, no. 3, pp. 258–263, 2022, doi: 10.17694/bajece.1028110.

[53] W. Alkishri, A. Abualkishik, and M. Al-Bahri, "Enhanced Image Processing and Fuzzy Logic Approach for Optimizing Driver Drowsiness Detection," *Appl. Comput. Intell. Soft Comput.*, vol. 2022, 2022, doi: 10.1155/2022/9551203.

[54] J. Huang, Z. X. Ji, X. Y. Peng, and L. Hu, "Driving Style Adaptive Lane-changing Trajectory Planning and Control," *Zhongguo Gonglu Xuebao/China J. Highw. Transp.*, vol. 32, no. 6, 2019, doi: 10.19721/j.cnki.1001-7372.2019.06.023.

[55] J. Huang, Y. Shang, and H. Chen, "Improved Viola-Jones face detection algorithm based on HoloLens," *Eurasip J. Image Video Process.*, vol. 2019, no. 1, 2019, doi: 10.1186/s13640-019-0435-6.

[56] S. O. Adeshina, H. Ibrahim, S. S. Teoh, and S. C. Hoo, "Custom face classification model for classroom using haar-like and lbp features with their performance comparisons," *Electron.*, vol. 10, no. 2, pp. 1–15, 2021, doi: 10.3390/electronics10020102.

[57] R. Gawande and S. Badotra, "Deep-Learning Approach for Efficient Eye-blink Detection with Hybrid Optimization Concept," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 6, pp. 782–795, 2022, doi: 10.14569/IJACSA.2022.0130693.

[58] P. Shinde and A. Raundale, "Secure Face and Liveness Detection with Criminal Identification for Security Systems," *Int. J. Recent Innov. Trends Comput. Commun.*, vol. 11, no. April, pp. 497–506, 2023, doi: 10.17762/ijritcc.v11i8s.7231.

[59] O. Z. Jie, L. T. Ming, and T. C. Wee, "Biometric Authentication based on Liveness Detection Using Face Landmarks and Deep Learning Model," *Int. J. Informatics Vis.*, vol. 7, no. 3–2, pp. 1057–1065, 2023, doi: 10.30630/joiv.7.3-2.2330.

[60] H. Elleuch, A. Wali, and A. M. Alimi, "Smart tablet monitoring by a real-time head movement and eye gestures recognition system," *Int. J. Comput. Digit. Syst.*, vol. 4, no. 3, pp. 183–192, 2015, doi: 10.12785/IJCDS/040305.

[61] A. L. M. Webb and P. B. Hibbard, "The effect of facial expression on contrast sensitivity: A behavioural investigation and extension of Hedger, Adams & Garner (2015)," *PLoS One*, vol. 14, no. 11, pp. 1–18, 2019, doi: 10.1371/journal.pone.0205621.

[62] K. Karilingappa, D. Jayadevappa, and S. Ganganna, "Human emotion detection and classification using modified Viola-Jones and convolution neural network," *IAES Int. J. Artif. Intell.*, vol. 12, no. 1, pp. 79–86, 2023, doi: 10.11591/ijai.v12.i1.pp79-86.

[63] F. Yan, M. Liu, C. Ding, Y. Wang, and L. Yan, "Driving style recognition based on electroencephalography data from a simulated driving experiment," *Front. Psychol.*, vol. 10, no. MAY, 2019, doi: 10.3389/fpsyg.2019.01254.

[64] T. Meireles and F. Dantas, "A low-cost prototype for driver fatigue detection," *Multimodal Technol. Interact.*, vol. 3, no. 1, 2019, doi: 10.3390/mti3010005.

[65] H. Purwanto, A. Nursikuwagus, D. Firmansyah, W. K. Wahyu Nurjaya, T. Ramdhany, and D. F. Shiddieq, "Design and Development of Mask Detectors in Effort to Prevent the Spread of Hepatitis Post-Covid-19 Pandemic using Viola-Jones Algorithm," *SSRG Int. J. Electron. Commun. Eng.*, vol. 10, no. 5, pp. 161–170, 2023, doi: 10.14445/23488549/IJECE-V10I5P115.

[66] R. P. M. D. Labib, S. Hadi, and P. D. Widayaka, "Low Cost System for Face Mask Detection Based Haar Cascade Classifier Method," *MATRIK J. Manajemen, Tek. Inform. dan Rekayasa Komput.*, vol. 21, no. 1, pp. 21–30, 2021, doi: 10.30812/matrik.v21i1.1187.

[67] R. Robin, A. Handinata, and W. Chandra, "Facial Recognition on System Prototype to Verify Users using Eigenface, Viola-Jones and Haar," *J. Comput. Networks, Archit. High Perform. Comput.*, vol. 3, no. 2, pp. 213–222, 2021, doi: 10.47709/cnahpc.v3i2.1058.

[68] N. D. Lakshmi, P. Nagubandi, M. Yelet, and K. V. Vardan, "Automated Attendance System Based on Facial Recognition using Viola-Jones Algorithm," *Asian J. Appl. Sci. Technol.*, vol. 06, no. 02, pp. 82–91, 2022, doi:

10.38177/ajast.2022.6210.

[69] A. Dixit and T. Kasbe, "Multi-feature based automatic facial expression recognition using deep convolutional neural network," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 25, no. 3, pp. 1406–1419, 2022, doi: 10.11591/ijeecs.v25.i3.pp1406-1419.

[70] B. Rudrusamy, H. C. Teoh, J. Y. Pang, T. H. Lee, and S. C. Chai, "IoT-Based Vehicle Monitoring and Driver Assistance System Framework for Safety and Smart Fleet Management," *Int. J. Integr. Eng.*, vol. 15, no. 1, pp. 391–403, 2023, doi: 10.30880/ijie.2023.15.01.035.

[71] S. Said, S. AlKork, T. Beyrouthy, M. Hassan, O. E. Abdellatif, and M. Fayek Abdraboo, "Real time eye tracking and detection- A driving assistance system," *Adv. Sci. Technol. Eng. Syst.*, vol. 3, no. 6, pp. 446–454, 2018, doi: 10.25046/aj030653.

[72] S. Kovalenko *et al.*, "OperatorEYEVP: Operator Dataset for Fatigue Detection Based on Eye Movements, Heart Rate Data, and Video Information," *Sensors*, vol. 23, no. 13, 2023, doi: 10.3390/s23136197.

[73] S. Junaedi and H. Akbar, "Driver Drowsiness Detection Based on Face Feature and PERCLOS," *J. Phys. Conf. Ser.*, vol. 1090, no. 1, 2018, doi: 10.1088/1742-6596/1090/1/012037.

[74] M. H. Alkinani, W. Z. Khan, and Q. Arshad, "Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges," *IEEE Access*, vol. 8, pp. 105008–105030, 2020, doi: 10.1109/ACCESS.2020.2999829.

[75] S. F. Zhao, W. Guo, and C. W. Zhang, "Extraction Method of Driver's Mental Component Based on Empirical Mode Decomposition and Approximate Entropy Statistic Characteristic in Vehicle Running State," *J. Adv. Transp.*, vol. 2017, 2017, doi: 10.1155/2017/9509213.

[76] L. Chen, P. Chen, and Z. Lin, "Artificial Intelligence in Education: A Review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[77] P. Shinde and A. R. Raundale, "Face and liveness detection with criminal identification using machine learning and image processing techniques for security system," *IAES Int. J. Artif. Intell.*, vol. 13, no. 1, pp. 722–729, 2024, doi: 10.11591/ijai.v13.i1.pp722-729.

[78] S. S. Yassin and Pooja, "Road accident prediction and model interpretation using a hybrid K-means and random forest algorithm approach," *SN Appl. Sci.*, vol. 2, no. 9, 2020, doi: 10.1007/s42452-020-3125-1.

[79] I. R. Adochiei *et al.*, "Drivers' drowsiness detection and warning systems for critical infrastructures," *2020 8th E-Health Bioeng. Conf. EHB 2020*, pp. 14–17, 2020, doi: 10.1109/EHB50910.2020.9280165.

[80] X. Zhao, Z. Wang, Z. Xu, Y. Wang, X. Li, and X. Qu, "Field experiments on longitudinal characteristics of human driver behavior following an autonomous vehicle," *Transp. Res. Part C Emerg. Technol.*, vol. 114, pp. 205–224, 2020, doi: 10.1016/j.trc.2020.02.018.

[81] V. R. Reddy Chirra, S. R. Uyyala, and V. K. Kishore Kolli, "Deep CNN: A machine learning approach for driver drowsiness detection based on eye state," *Rev. d'Intelligence Artif.*, vol. 33, no. 6, pp. 461–466, 2019, doi: 10.18280/ria.330609.

[82] A. Kumar, "ISCAIE 2014 - 2014 IEEE Symposium on Computer Applications and Industrial Electronics," *ISCAIE 2014 - 2014 IEEE Symp. Comput. Appl. Ind. Electron.*, p. 237, 2015.

[83] S. Badrloo, M. Varshosaz, S. Pirasteh, and J. Li, "Image-Based Obstacle Detection Methods for the Safe Navigation of Unmanned Vehicles: A Review," *Remote Sens.*, vol. 14, no. 15, pp. 1–26, 2022, doi: 10.3390/rs14153824.

[84] B. Akrout and W. Mahdi, "A novel approach for driver fatigue detection based on visual characteristics analysis," *J. Ambient Intell. Humaniz. Comput.*, vol. 14, no. 1, pp. 527–552, 2023, doi: 10.1007/s12652-021-03311-9.

[85] S. Khairnar, S. Gite, K. Kotecha, and S. D. Thepade, "Face Liveness Detection Using Artificial Intelligence Techniques: A Systematic Literature Review and Future Directions," *Big Data Cogn. Comput.*, vol. 7, no. 1, 2023, doi: 10.3390/bdcc7010037.

[86] W. Xiao, H. Liu, Z. Ma, W. Chen, and J. Hou, "FPIRST: Fatigue Driving Recognition Method Based on Feature Parameter Images and a Residual Swin Transformer," *Sensors*, vol. 24, no. 2, 2024, doi: 10.3390/s24020636.

[87] S. Liu, Y. Wang, Q. Yu, J. Zhan, H. Liu, and J. Liu, "A Driver Fatigue Detection Algorithm Based on Dynamic Tracking of Small Facial Targets Using YOLOv7," *IEICE Trans. Inf. Syst.*, vol. E106.D, no. 11, pp. 1881–1890, 2023, doi: 10.1587/transinf.2023EDP7093.

[88] J. Hollósi, Á. Ballagi, G. Kovács, S. Fischer, and V. Nagy, "Face Detection Using a Capsule Network for Driver

Monitoring Application," *Computers*, vol. 12, no. 8, 2023, doi: 10.3390/computers12080161.

[89] H. A. Ahmed, M. S. Croock, and M. A. Noaman Al-Hayanni, "Intelligent Vehicle Driver Face and Conscious Recognition," *Rev. d'Intelligence Artif.*, vol. 37, no. 6, pp. 1483–1492, 2023, doi: 10.18280/ria.370612.

[90] N. T. N. Quyen, T. D. Linh, V. H. Phuc, and N. Van Nam, "SHELF: Combination of Shape Fitting and Heatmap Regression for Landmark Detection in Human Face," *EAI Endorsed Trans. Ind. Networks Intell. Syst.*, vol. 10, no. 3, pp. 1–10, 2023, doi: 10.4108/eetinis.v10i3.3863.

[91] B. E. B. Lim, K. W. Ng, and S. L. Ng, "Drowsiness Detection System through Eye and Mouth Analysis," *Int. J. Informatics Vis.*, vol. 7, no. 4, pp. 2489–2497, 2023, doi: 10.30630/joiv.7.4.2288.

[92] B. Bousarhane and D. Bouzidi, "RF-CNNS: Thin Deep Learning Networks For Accelerating Traffic Signs Recognition," *J. Comput. Sci.*, vol. 19, no. 10, pp. 1263–1282, 2023, doi: 10.3844/JCSSP.2023.1263.1282.

[93] S. M. Shah, S. Zhaoyun, K. Zaman, A. Hussain, M. Shoaib, and P. Lili, "A Driver Gaze Estimation Method Based on Deep Learning," *Sensors*, vol. 22, no. 10, pp. 1–22, 2022, doi: 10.3390/s22103959.

[94] H. Xiao *et al.*, "On-Road Driver Emotion Recognition Using Facial Expression," *Appl. Sci.*, vol. 12, no. 2, 2022, doi: 10.3390/app12020807.

[95] W. Xiao, H. Liu, Z. Ma, W. Chen, C. Sun, and B. Shi, "Fatigue Driving Recognition Method Based on Multi-Scale Facial Landmark Detector," *Electron.*, vol. 11, no. 24, 2022, doi: 10.3390/electronics11244103.

[96] L. Ulrich *et al.*, "Can adas distract driver's attention? An rgb-d camera and deep learning-based analysis," *Appl. Sci.*, vol. 11, no. 24, 2021, doi: 10.3390/app112411587.

[97] E. Fu, X. Li, Z. Yao, Y. Ren, Y. Wu, and Q. Fan, "Personnel emotion recognition model for Internet of vehicles security monitoring in community public space," *EURASIP J. Adv. Signal Process.*, vol. 2021, no. 1, 2021, doi: 10.1186/s13634-021-00789-5.

[98] R. J. Doniec, S. Sieciński, K. M. Duraj, N. J. Piaseczna, K. Mocny-Pachońska, and E. J. Tkacz, "Recognition of drivers' activity based on 1d convolutional neural network," *Electron.*, vol. 9, no. 12, pp. 1–17, 2020, doi: 10.3390/electronics9122002.

[99] A. A. Bamidele *et al.*, "Non-intrusive driver drowsiness detection based on face and eye tracking," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 7, pp. 549–569, 2019, doi: 10.14569/ijacsa.2019.0100775.

[100] J. Wang, X. Yu, Q. Liu, and Z. Yang, "Research on key technologies of intelligent transportation based on image recognition and anti-fatigue driving," *Eurasip J. Image Video Process.*, vol. 2019, no. 1, 2019, doi: 10.1186/s13640-018-0403-6.